



A Two-Stage Decomposition of High School Timetabling applied to cases in Denmark

Sørensen, Matias; Dahms, Florian H.W.

Published in:
Computers and Operations Research

Link to article, DOI:
[10.1016/j.cor.2013.08.025](https://doi.org/10.1016/j.cor.2013.08.025)

Publication date:
2014

[Link back to DTU Orbit](#)

Citation (APA):
Sørensen, M., & Dahms, F. H. W. (2014). A Two-Stage Decomposition of High School Timetabling applied to cases in Denmark. *Computers and Operations Research*, 43, 36–49. <https://doi.org/10.1016/j.cor.2013.08.025>

General rights

Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

- Users may download and print one copy of any publication from the public portal for the purpose of private study or research.
- You may not further distribute the material or use it for any profit-making activity or commercial gain
- You may freely distribute the URL identifying the publication in the public portal

If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

A Two-Stage Decomposition of High School Timetabling applied to cases in Denmark

Matias Sørensen^{a,b,*}, Florian H.W. Dahms^c

^a Section of Operations Research, Department of Management Engineering, Technical University of Denmark, DK-2800 Kgs. Lyngby, Denmark

^b MaCom A/S, Vesterbrogade 48, 1., DK-1620 Copenhagen V, Denmark

^c Chair of Operations Research, RWTH Aachen University, Kackertstraße 7, 52072 Aachen, Germany

Abstract

Integer Programming (IP) has been used to model educational timetabling problems since the very early days of Operations Research. It is well recognized that these IP models in general are hard to solve, and this area of research is dominated by heuristic solution approaches. In this paper a *Two-Stage Decomposition* of an IP model for a practical case of high school timetabling is shown. This particular timetabling problem consists of assigning lectures to both a timeslot and a classroom, which is modeled using a very large amount of binary variables. The decomposition splits this model into two separate problems (Stage I and Stage II) with far less variables. These two separate problems are solved in sequence, such that the solution for the Stage I model is given as input to the Stage II model, implying that irreversible decisions are made in Stage I. However, the objective of the Stage II model is partly incorporated in the Stage I model by exploiting that Stage II can be seen as a *minimum weight maximum matching* problem in a bipartite graph. This theoretically strengthens the decomposition in terms of global optimality. The approach relies on Hall's theorem for the existence of matchings in bipartite graphs, which in its basic form yields an exponential amount of constraints in the Stage I model. However, it is shown that only a small subset of these constraints is needed, making the decomposition tractable in practice for IP solvers. To evaluate the decomposition, 100 real-life problem instances from the database of the high school ERP system Lectio are used. Computational results show that the decomposition performs significantly better than solving the original IP, in terms of both found solutions and bounds.

Keywords: High School Timetabling, Integer Programming, Decomposition, Bipartite Matching

1. Introduction

Integer Programming (IP) has been used to model educational timetabling problems since the very early days of Operations Research (see e.g. Gotlieb (1962) and Lawrie (1969)). It is well recognized that these IP models in general are hard to solve (most forms of educational timetabling are in fact \mathcal{NP} -hard (Bardadym (1996))), and this area of research is dominated by heuristic solution approaches.

In this paper a large IP model for a real-world case of high school timetabling is considered, which has previously been shown to be a challenge for state-of-the-art MIP solvers. We consider a basic version of this IP, which includes the essential constraints of most timetabling problems. An innovative decomposition of this model is shown, which proves to be more efficient to solve.

When facing a hard IP model, decomposition is a commonly used tool to help speed up the solution procedure. Perhaps the most successful decomposition method in recent years is Column Generation (CG). However, not many papers on CG and timetabling models are found in the literature, and it seems that only relatively small instances have been attempted. Papoutsis et al. (2003) uses CG to solve a Greek case of high school timetabling, with the largest instance containing 9 class section, 21 teachers and 306 teaching hours. Santos et al. (2012) handle larger instances,

*Corresponding author

Email address: mss@dtu.dk (Matias Sørensen)

but only generate lower bounds. Qualizza and Serafini (2005) describe a CG procedure for a university timetabling problem with 63 courses and 25 timeslots. The real-world instances considered in this paper are of much larger size.

A crucial part of a CG procedure is the identification of a block-diagonal structure in the problem, otherwise the CG procedure is most likely not efficient. For the high school timetabling problem described in this paper, it has not been possible to identify such a structure. Therefore this paper shows a different type of decomposition, a *Two-Stage Decomposition* (TSD). Such an approach was first used for timetabling applications in Lach and Lübbecke (2008) and Lach and Lübbecke (2012) with great success for the *curriculum-based university course* timetabling problem. The goal of this paper will be to modify the aforementioned approach to be applicable for the high school timetabling problem - giving special attention to the high school system in Denmark.

The considered timetabling problem essentially consists of assigning lectures to rooms and timeslots, which is commonly modeled using a very large amount of binary variables. There are three key points to the TSD:

- By substitution, the total amount of variables is significantly reduced, while linearity is maintained.
- Instead of solving the entire model at once, it can be solved in a two-stage fashion. I.e. both the set of variables and constraints are divided into two distinct sets, corresponding to two smaller IPs (denoted *Stage I* and *Stage II*, respectively).
- It will be evident that, except for two soft-constraints, this decomposition maintains optimality of the original model.

The outline of the TSD is to first solve Stage I, which provides a solution where lectures are assigned to timeslots. This partial solution is given as input to Stage II, which will assign rooms to the lectures, obtaining a solution for the original problem. The drawback of this decomposition is that the timeslots assigned to lectures in Stage I are considered as fixed by the Stage II model, which might prevent an optimal allocation of rooms to lectures. However, by exploiting the structure of the Stage II model, the Stage I model can be constrained in such a way that some penalties for assigning rooms to lectures are handled implicitly. Note that if all penalties for room assigning could be handled implicitly, the approach would be exact. However, two soft-constraints are not fully incorporated, so only a lower bound on the room penalties are known by the Stage I model. In fact, one of these soft-constraints are not handled at all by the described approach. Despite this, it seems likely that incorporating this lower bound in the Stage I model will provide better results overall (assuming that computing the lower bound does not have very bad influence on the computational efforts of the used IP solver). I.e. instead of the Stage I model being completely unaware of the penalties for room allocation, it seems better to at least incorporate some of them. Furthermore, the decomposition of the problem into two smaller problems presents a big advantage in terms of reduction in the number of variables. Therefore the overall benefits of the TSD out-weigh the downsides, and computational results will show that it is indeed way more effective than solving the original IP.

The contributions of this paper are the following: 1) It is shown that the approach from Lach and Lübbecke (2008) can also be applied to a high school timetabling problem originating from a practical setting, and by extensive computational results it is argued that the TSD is more effective than solving the original IP. Notice that a similar composition is briefly mentioned in Sørensen and Stidsen (2013) for the same high school timetabling problem, but this paper enhances the approach such that the theoretical maximum gap from optimality is narrowed. The presented approach turns out to be the most efficient exact algorithm for the problem so far. 2) Generally, it is shown how this type of decomposition can be applied to models with set-packing structure, by modifying the underlying equations originating from Hall's Theorem for matchings in bipartite graphs. 3) It is shown how the room-priorities of lectures can be handled, by adding a lower bound on the corresponding penalties to the Stage I model. This facilitates the quality of the solutions found, as shown by the computational results.

We expect that the basic structure required for applying the TSD can be found in other timetabling problems as well, and therefore the decomposition can potentially be used more broadly than the case of high school timetabling shown in this paper. This seems likely because the essential constraints used in the decomposition are among the most common ones found in timetabling problems.

The paper is structured as follows. First related papers are described in Section 2. The basic IP model is introduced in Section 3, including the essential constraints. Section 4 shows the TSD of this model, and derives the lower bound on room allocation penalties for the Stage I model. Section 5 extends the model so it encapsulates a practical version

of the high school timetabling problem, defined by the online high school administration system Lectio. Section 6 shows computational results, comparing the decomposition to previous approaches for 100 problem instances taken from the Lectio database. Section 7 concludes on our findings.

2. Related work

Integer Programming has been used to model various educational timetabling problems. However, heuristics are still the most popular method for these problems, see surveys Schaerf (1999) and Pillay (2013). In terms of IP, de Werra (1985) describes what is called 'a simple model' for the class-teacher problem, and existence of solutions is proven under certain circumstances using graph theoretical models. The problems considered are feasibility problems, and soft constraints are not added to the models. Birbas et al. (1997) describes a 'fully defined' IP model for Greek secondary schools, which is evaluated on five different schools with success. Avella et al. (2007) formulates an IP model which is used to solve small instances of various origin. The IP is solved within a VLSN algorithm, with good results.

For the related university course timetabling problem, Daskalaki et al. (2004) presents a model which schedules courses to timeslots and classrooms, using many so called *operational rules*. Three different problem instances of significant size are all solved to optimality using CPLEX. MirHassani (2006) describes the problem for an Iranian university, and reports good results by applying the XA solver. In Dimopoulou and Miliotis (2001) an IP model is used to solve the timetabling problem for The Athens University of Economics and Business.

Decomposition of IP models for educational timetabling is not a very well researched topic. Burke et al. (2010) state that: *In the timetabling community, the "times first, rooms second" decomposition is a standard procedure.* However, it seems that this procedure has not been applied much in context of IP models. Burke and Newall (1999) apply the procedure in context of an Evolutionary Algorithm for Examination Timetabling. In terms of multistage-decompositions, the importance of Lach and Lübbecke (2008) and Lach and Lübbecke (2012) has already been discussed. Carter (1983) presents an interesting decomposition algorithm for course timetabling with elective courses. Stating the problem in terms of a vertex coloring problem facilitates the decomposition of the graph by cliques, such that the subproblem defined by each clique is solved separately.

In Burke et al. (2010), experiments are conducted on disabling different combinations of soft-constraint penalties of the *Udine Course Timetabling Problem*, including one where all room penalties on room allocation are disabled. Thereby a similar decomposition to that of Lach and Lübbecke (2012) is obtained.

Daskalaki and Birbas (2005) presents an approach for university timetabling, where courses are first assigned to days (skipping some requirements for compactness), and in the following stage the timetable for each day is treated locally (enforcing the compactness). Convincing computational results are shown. In Birbas et al. (2009), a high school timetabling problem is solved by first allocating 'work shifts' to teachers, and then solving the actual timetabling problem. This is related to the type of decomposition performed in this paper. Badri (1996) uses a related approach for university course timetabling, where *faculties* are first assigned to courses, and then faculties are assigned to timeslots. However the problems solved are tiny.

Recently, high school timetabling received attention in the *International Timetabling Competition 2011* (ITC2011), see Post et al. (2012a). This competition built upon an uniform format for formulating problem instances (and their solutions), known as *XHSTT* (Post et al. (2012b)). Currently, around 50 problem instances are available in this format. The problem considered in this paper deviates from the XHSTT format in several important ways, which is beyond the scope of this section to elaborate on. Even though many researches participated in ITC2011, it seems that all were applying heuristics.

3. An Integer Programming Model for High School Timetabling

As the origin for our approach lies the IP model presented in Sørensen and Stidsen (2013). To make a clear presentation of the TSD, this IP model is reduced to its essential parts, which is described in the following. In Section 5, the full IP model is shown in context of the TSD.

A set of *events* \mathcal{E} is given. Each event generally represents one lecture, which is defined as a meeting between specific *resources*, with a certain subject as teaching-objective. The set of resources is denoted \mathcal{A} . The goal of the high

school timetabling problem is to assign each event to a room and to a timeslot, such that no conflicts among resources occur. The set of rooms and timeslots are denoted \mathcal{R} and \mathcal{T} , respectively. The decision variable $x_{e,r,t} \in \{0, 1\}$ takes value 1 if event $e \in \mathcal{E}$ is assigned room $r \in \mathcal{R}$ and timeslot $t \in \mathcal{T}$. To ensure a feasible solution exists, both the set of timeslots \mathcal{T} and the set of rooms \mathcal{R} are extended with a single dummy element, i.e. $\mathcal{T} = \{\mathcal{T} \cup t_D\}$ and $\mathcal{R} = \{\mathcal{R} \cup r_D\}$. This should be interpreted in the way that assigning to these dummy-elements actually means that no timeslot/room was assigned to the event. Thereby the goal of the IP is to assign as many events *as possible* to a timeslot and/or a room. From a practical point of view this is desirable, as the model is used in a decision support context where it might not be evident how to handle infeasibility. $\phi_{e,t} \in \mathbb{R}^+$ denotes the penalty for assigning event $e \in \mathcal{E}$ to timeslot $t \in \mathcal{T}$, and $\pi_{e,r} \in \mathbb{R}^+$ denotes the penalty for assigning event $e \in \mathcal{E}$ to room $r \in \mathcal{R}$. Major penalties are given for assignments to the dummy-elements, i.e.

$$\phi_{e,t_D} \gg \phi_{e,t} \quad \forall e \in \mathcal{E}, t \in \mathcal{T} \setminus t_D \quad (1)$$

$$\pi_{e,r_D} \gg \pi_{e,r} \quad \forall e \in \mathcal{E}, r \in \mathcal{R} \setminus r_D \quad (2)$$

A room might be unavailable in certain timeslots, indicated by the binary parameter $G_{r,t} \in \{0, 1\}$, which takes value 1 if room $r \in \mathcal{R}$ is available in timeslot $t \in \mathcal{T}$, and 0 otherwise. Furthermore, a set of eligible rooms exists for each event. Let parameter $K_{e,r} \in \{0, 1\}$ take value 1 if event $e \in \mathcal{E}$ can take place in room $r \in \mathcal{R}$, and 0 otherwise. Each event requires a fixed set of resources. Let $E'_a, a \in \mathcal{A}$, denote the set of events where resource a participates.

We include in the model a set of constraints which will be described later, denoted by the constraint-set P_{other} , slightly abusing notation. These constraints define various other important criteria, such as forbidden timeslots for certain events, events which must be placed in the same timeslots, etc. Since these constraints are not required for describing the decomposition, their definitions are postponed to Section 5. We allow the set of constraints P_{other} to also denote soft-constraints (i.e. constraints which result in a weighted penalty in the objective function if it is not fulfilled). Thereby these constraints contain all necessary for conditions for modeling the timetabling instances in question, and represents a large set of distinct types of constraints. It will be argued in the next section that these constraints can be handled in the decomposition such that optimality of the IP model is not lost, with one exception.

Model (3) shows the IP model.

IP Model for High School Timetabling (3)

$$\min \quad w = \sum_{e \in \mathcal{E}, r \in \mathcal{R}, t \in \mathcal{T}} (\phi_{e,t} + \pi_{e,r}) x_{e,r,t} \quad (3a)$$

s.t.

$$\text{(one time/room)} \quad \sum_{r \in \mathcal{R}, t \in \mathcal{T}} x_{e,r,t} = 1 \quad \forall e \in \mathcal{E} \quad (3b)$$

$$\text{(resource conf.)} \quad \sum_{r \in \mathcal{R}, e \in E'_a} x_{e,r,t} \leq 1 \quad \forall a \in \mathcal{A}, t \in \mathcal{T} \setminus t_D \quad (3c)$$

$$\text{(room conf.)} \quad \sum_{e \in \mathcal{E}} x_{e,r,t} \leq G_{r,t} \quad \forall r \in \mathcal{R} \setminus r_D, t \in \mathcal{T} \setminus t_D \quad (3d)$$

$$\text{(eligible rooms)} \quad \sum_{t \in \mathcal{T}} x_{e,r,t} \leq K_{e,r} \quad \forall e \in \mathcal{E}, r \in \mathcal{R} \quad (3e)$$

$$x_{e,r,t} \in P_{\text{other}} \quad (3f)$$

$$x_{e,r,t} \in \{0, 1\} \quad (3g)$$

The objective of the model is to minimize the overall penalty for assignments, given by (3a). Constraint (3b) specifies that each event must be assigned exactly one timeslot and one room. Events which require the same resource cannot be scheduled simultaneously (except in the dummy-timeslot), which is ensured by constraint (3c). A room cannot be used by more than one event in each timeslot. This is specified in constraint (3d). The requirement for eligible rooms is specified in constraint (3e). Constraint (3f) specifies that constraints P_{other} should be respected.

Theorem 3.1. *The High School Timetabling Problem as specified in (3) is NP-hard.*

Proof. We conduct a reduction from Vertex Coloring. Let $G = (V, E)$ be an arbitrary graph and k be an arbitrary number. The question of the coloring problem would now be whether it is possible to color G with k colors, such that no two adjacent vertices share the same color.

Now construct a High School Timetabling instance in the following way:

- Let there be an event for every vertex, i.e. $\mathcal{E} = V$.
- Make sure there are enough rooms for all events, therefore create a room for every event (i.e. $|\mathcal{R}| = |\mathcal{E}|$) and make sure all events fit in all rooms (i.e. $K_{e,r} = 1 \forall e \in \mathcal{E}, r \in \mathcal{R}$), and that all rooms are available in all timeslots (i.e. $G_{r,t} = 1 \forall e \in \mathcal{E}, r \in \mathcal{R}$).
- For every edge $\{v_1, v_2\} \in E$ we create a resource in \mathcal{A} (i.e. $\mathcal{A} = E$). The events using this resource will be the vertices connected by the edge (i.e. $E'_{\{v_1, v_2\}} = \{v_1, v_2\}$).
- We use exactly k timeslots (i.e. $\mathcal{T} = \{1, \dots, k\}$).
- The additional constraints P_{other} can be dropped without loss of generality, as we impose no other restrictions on the timetabling instance. Also as we only search for a feasible solution, the soft constraints can easily be ignored.

Now we have a direct relation between the Vertex Coloring problem and the new timetabling instance. A solution of one problem can be transformed into a solution of the other by translating the colors of the vertices into timeslots, and vice versa. The rooms pose no restriction as every event can be scheduled in its own room.

Therefore solving the timetabling instance would result in solving the Vertex Coloring Problem, and the High School Timetabling problem is \mathcal{NP} -hard. \square

Here we remark that Model (3) encapsulates many of the basic constraints required by most timetabling problems. If we for instance consider the XHSTT format, the basic requirement is to assign events to timeslots and resources (corresponding to rooms in our cases), subject to no clashes between resources. Therefore it is believed that the type of decomposition considered in this paper can in principle be applied to other timetabling problems as well.

4. Two-Stage Decomposition of the Integer Programming model

The TSD of Model (3) is performed as follows. The model is split into two stages; In Stage I, events are assigned to timeslots, and in Stage II, events are assigned to rooms. The respective decision variables for these stages are the following; $y_{e,t} \in \{0, 1\}$ takes value 1 if event $e \in \mathcal{E}$ is assigned timeslot $t \in \mathcal{T}$, and 0 otherwise; $z_{e,r} \in \{0, 1\}$ takes value 1 if event $e \in \mathcal{E}$ is assigned room $r \in \mathcal{R}$, and 0 otherwise. This means that constraints (3b) and (3c) are part of Stage I, and constraints (3d) and (3e) are part of Stage II.

As for constraints (3f), defined by the set P_{other} , it is assumed that each of the constraints in P_{other} is either only touching the assignment of events to timeslots (denoted P_{timeslot}) or the assignment of events to rooms (denoted P_{room}). It is shown in Section 5 that this assumption holds, with one exception. This means that constraints P_{timeslot} can be fully stated in terms of variable $y_{e,t}$, and constraints P_{room} can be fully stated in terms of variable $z_{e,r}$. As constraints P_{timeslot} are part of Stage I, these are handled optimally. This is different for P_{room} , as those constraints are harder to consider during Stage I. We will therefore address them with greater care in the next sections and show how we can add weighted room allocations to the decomposed model as a good approximation.

The solution obtained from the Stage I model is given as a parameter to the Stage II model, denoted $y_{e,t}^*$. The advantage of this approach is the huge reduction in the number of variables in both stages, which results in a significantly decreased solving time. The following substitution of variables are made:

$$\sum_{r \in \mathcal{R}} x_{e,r,t} = y_{e,t} \quad (\text{Stage I}) \quad (4)$$

$$x_{e,r,t} = y_{e,t}^* z_{e,r} \quad (\text{Stage II}) \quad (5)$$

The objective (3a) of the original model defines a natural objective for both Stage I and Stage II, since it can be split into two independent expressions (denoted w^I and w^{II} , respectively). If this was not the case (e.g. if an event had different priorities for rooms depending on the timeslot it was assigned), it would complicate matters in terms of the Stage I model.

To sum up, Models (6) and (7) show Stage I and Stage II, respectively.

Stage I (6)

$$\min \quad w^I = \sum_{e \in \mathcal{E}, t \in \mathcal{T}} \phi_{e,t} y_{e,t} \quad (6a)$$

s.t.

$$\text{(one timeslot)} \quad \sum_{t \in \mathcal{T}} y_{e,t} = 1 \quad \forall e \in \mathcal{E} \quad (6b)$$

$$\text{(resource conf.)} \quad \sum_{e \in E'_a} y_{e,t} \leq 1 \quad \forall a \in \mathcal{A}, t \in \mathcal{T} \setminus t_D \quad (6c)$$

$$y_{e,t} \in P_{\text{timeslot}} \quad (6d)$$

$$y_{e,t} \in \{0, 1\} \quad (6e)$$

Stage II (solution from Stage I is denoted $y_{e,t}^$)* (7)

$$\min \quad w^{II} = \sum_{e \in \mathcal{E}, r \in \mathcal{R}} \pi_{e,r} z_{e,r} \quad (7a)$$

s.t.

$$\text{(one room)} \quad \sum_{r \in \mathcal{R}} z_{e,r} = 1 \quad \forall e \in \mathcal{E} \quad (7b)$$

$$\text{(room conf.)} \quad \sum_{e \in \mathcal{E}} y_{e,t}^* z_{e,r} \leq G_{r,t} \quad \forall r \in \mathcal{R} \setminus r_D, t \in \mathcal{T} \setminus t_D \quad (7c)$$

$$\text{(eligible rooms)} \quad z_{e,r} \leq K_{e,r} \quad \forall e \in \mathcal{E}, r \in \mathcal{R} \quad (7d)$$

$$z_{e,r} \in P_{\text{room}} \quad (7e)$$

$$z_{e,r} \in \{0, 1\} \quad (7f)$$

The outline of the TSD is shown in Figure 1. For a variable x the star-suffixed version x^* denotes a feasible solution. Stage I is solved using a MIP solver to obtain a solution $y_{e,t}^*$, which is given as input to the Stage II model. Note that Stage I possesses the coloring structure from theorem 3.1. Therefore Stage I is already a hard problem in its most basic form. Furthermore the value of the LP-relaxation of the Stage I model (denoted w_{LP}^I) is a lower bound on the original model, as the Stage I model can be seen as a relaxation. Solving the Stage II model subject to the solution of the Stage I model obtains a solution $z_{e,t}^*$, and a solution to the original model $x_{e,r,t}^*$ can then be derived by equations (4) and (5).

For this paper we will solve Stage II using the specified IP even though we have not established its complexity yet. But as constructing a polynomial time algorithm for Stage II that can cope with all the additional constraints would be out of this papers scope we will postpone this to a potentially later point in time. In the computational results section we will see that solving Stage II will not be the time-wise bottleneck anyhow.

As previously discussed, the penalties for room allocation can be implicitly handled in Stage I, which is described in Section 4.1. This extension of Stage I will not only allow better solutions to be found, but possibly also improvements in the bounds found by means of the LP relaxation.

As an alternative approach, we remark that an iterative procedure could in principle be used, such that the solution obtained from the Stage II model is given as input to the Stage I model, and the whole procedure is repeated. It is however unclear how the input from the Stage II model should effect the Stage I model to obtain convergence towards better solutions in terms of the overall objective. Furthermore, such an approach would require that both Stage I and Stage II can be solved 'quickly' (for the practical problem treated in this paper, computational results will show that this is in fact not the case for the Stage I model).

4.1. Extending Stage I with room allocation

The key idea behind extending Stage I with room allocation penalties is to consider Stage II as a matching problem in a bipartite graph. Constraints (7e) are set aside in the following, as they have not been defined yet. However, it will

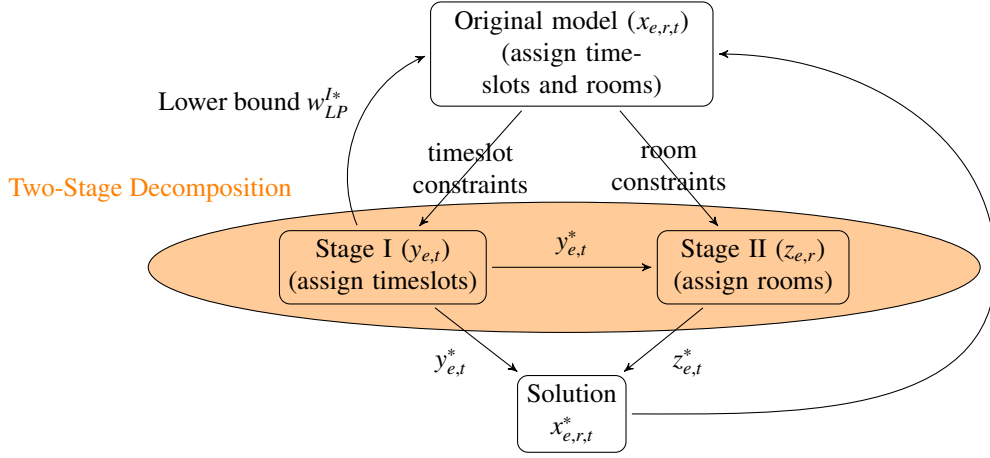


Figure 1: Two-Stage Decomposition flow chart.

be seen later that these constraints does not fully obey the matching problem structure, and therefore Stage II must be solved with a MIP solver. This means that the room penalties are only partly incorporated in Stage I, but still this seems better than having Stage I being totally unaware of these penalties, as already discussed in Section 1.

Some basic graph notation is introduced in the following. A graph is *bipartite* if its set of vertices can be partitioned into two sets A and B , such that every edge has one endpoint in A , and the other endpoint in B . A *matching* in a graph is a set of edges such that no two of these edges share endpoints. A *maximum matching* is a matching that contains the largest possible number of edges. The *matching number* $\nu(G)$ of graph G is the number of edges in a maximum matching. For a graph with edge-weights, a *minimum weighted maximum matching* is a maximum matching where the sum of the weights on the edges of the matching is minimal.

In the Stage II model (7), notice first that the only constraint which treats timeslots is constraint (7c). Since this constraint applies to timeslots individually, Model (7) can be split into $|\mathcal{T}|$ independent optimization problems. Second, assume that the minimum weighted maximum matching problem of the weighted bipartite graph $G_t = (\mathcal{E} \cup \bar{\mathcal{R}}, E_t)$ fully describes the optimization problem of timeslot t of Model (7). To recognize this, let \mathcal{R}_D be the set of $|\mathcal{E}|$ distinct dummy-rooms. I.e. for each event a dummy-room is created (and a corresponding edge is added to the graph) to ensure a matching of every event to a room will always exist. Hence the room-vertices of graph G_t is given by $\bar{\mathcal{R}} = \mathcal{R} \cup \mathcal{R}_D$. The set of edges is given by (skipping edge definitions for the dummy-room vertices) $E_t = \{e \in \mathcal{E}, r \in \mathcal{R} \mid K_{e,r} = 1 \wedge G_{r,t} = 1\}$, and the weight on each edge is given by $\pi_{e,r}$. The goal of the matching problem is to select a maximum matching with minimum weight. A trivial maximum matching will assign every event to the dummy-room. Clearly this resembles component $t \in \mathcal{T}$ of Model (7).

Stating the Stage II model in terms of this graph allows us to exploit some well-known properties of matching problems in bipartite graphs. In the following, notation is simplified by dropping the t -index where applicable, i.e. we write G instead of G_t and E instead of E_t . Denote by $\Gamma(S)$ the neighbors of event-nodes $S \subseteq \mathcal{E}$ in graph G , i.e. $\Gamma(S) = \{i \in \bar{\mathcal{R}} \mid j \in S, (i, j) \in E\}$. Hence $\Gamma(S) \subseteq \bar{\mathcal{R}}$. The well-known theorem of Hall states that a bipartite graph $G = (\mathcal{E} \cup \bar{\mathcal{R}}, E)$ has a matching of all vertices \mathcal{E} into $\bar{\mathcal{R}}$ if and only if $|\Gamma(S)| \geq |S| \quad \forall S \subseteq \mathcal{E}$. Observe that for timeslot $t \in \mathcal{T}$, the variable $y_{e,t}$ determines whether event $e \in \mathcal{E}$ is part of graph G . Lach and Lübbecke (2012) used this theorem to add constraints of the form

$$\sum_{e \in S} y_{e,t} \leq |\Gamma(S)| \quad \forall S \subseteq \mathcal{E}, t \in \mathcal{T} \quad (8)$$

to the Stage I model to guarantee that the Stage I model would yield a feasible matching problem for every component $t \in \mathcal{T}$ of the Stage II model. However, such constraints are redundant in our case, as we are guaranteeing that no matter how $y_{e,t}$ is selected, a feasible matching will always exist (due to the dummy-rooms). Instead we modify the expression (8) to provide a lower bound on the weighted matching problem.

For the bipartite graph $G = (\mathcal{E} \cup \bar{\mathcal{R}}, E)$ (the edge-weights are set aside for now), let the *deficiency* of a vertex set $S \subseteq \mathcal{E}$ be defined as $\text{def}(S) = |S| - |\Gamma(S)|$. Let the deficiency of G be defined as $\text{def}(G) = \max_{S \subseteq \mathcal{E}} \text{def}(S)$. Theorem 1.3.1 of Lovász and Plummer (2009) states the following:

Theorem 4.1. *The matching number of the bipartite graph $G = (\mathcal{E} \cup \bar{\mathcal{R}}, E)$, is $\nu(G) = |\mathcal{E}| - \text{def}(G)$.*

I.e. for the bipartite graph G , $\text{def}(G)$ denotes the amount of vertices which are not matched in the maximum matching.

Let \mathcal{W} denote the ordered set of different values found in $\pi_{e,r}$, i.e.

$$\mathcal{W} = \{w \in \mathbb{R}^+ \mid \exists e \in \mathcal{E}, \exists r \in \mathcal{R} : \pi_{e,r} = w\} \quad (9)$$

$$w_i < w_j \Leftrightarrow \text{ord}(w_i) < \text{ord}(w_j) \quad \forall (w_i, w_j) \in \mathcal{W} \quad (10)$$

Notice that no restrictions are posed on the amount of different values found, but it should be remarked that for our practical case, the cardinality of \mathcal{W} is small (typically below 10).

The bipartite graph G is split into subgraphs, one subgraph for each $w \in \mathcal{W}$. A subgraph is denoted as $G_{\leq w} = (\mathcal{E} \cup \bar{\mathcal{R}}, E_{\leq w})$, where the set of edges are those with at least weight w ,

$$E_{\leq w} = \{(e, r) \in E \mid \pi_{e,r} \leq w\} \quad (11)$$

By these definitions, it is clear that

$$|\Gamma(G_{\leq w_1})| \leq |\Gamma(G_{\leq w_2})| \leq \dots \Rightarrow \quad (12)$$

$$\text{def}(G_{\leq w_1}) \geq \text{def}(G_{\leq w_2}) \geq \dots \quad (13)$$

Using the deficiencies of these subgraphs, a lower bound on the minimum weight maximum matching can be stated. Let $a_w \in \mathbb{N}_0$ be defined as

$$a_{w_i} = \begin{cases} \nu(G_{\leq w_i}) - \nu(G_{\leq w_{i-1}}) & = \text{def}(G_{\leq w_{i-1}}) - \text{def}(G_{\leq w_i}) & \text{if } i > 1 \\ \nu(G_{\leq w_1}) & = |\mathcal{E}| - \text{def}(G_{\leq w_1}) & \text{otherwise} \end{cases} \quad (14)$$

The intuition behind a_w is to measure the change in the matching number when edges with weight w are added to the subgraph $G_{\leq w_{i-1}}$. Note that $0 \leq a_w \leq |\mathcal{E}|$ for any $w \in \mathcal{W}$, as $0 \leq \text{def}(G_{\leq w}) \leq |\mathcal{E}|$.

Theorem 4.2. *The quantity*

$$\sum_{w \in \mathcal{W}} w \cdot a_w$$

is a lower bound on a minimum weight maximum matching in the edge-weighted bipartite graph G .

Proof. Assume for contradiction there exists a maximum matching M with lower weight, i.e.

$$\sum_{e \in M} w_e < \sum_{w \in \mathcal{W}} w \cdot a_w$$

Let b_w denote the number of edges in M of weight lesser or equal w , i.e.

$$b_w = |\{e \in M : w_e \leq w\}|$$

Let k be the smallest number such that,

$$b_{w_k} > \sum_{i=1}^k a_{w_i}$$

This number must exist since M is a cheaper matching. For the subgraph $G_{\leq w_k}$, b_{w_k} can never exceed the matching number $\nu(G_{\leq w_k})$ (by Theorem 4.1). We say 'exceed' as the matching might not include precisely $\nu(G_{\leq w_k})$ edges of weight lesser or equal w_k . This gives:

$$\begin{aligned}
b_{w_k} &\leq \nu(G_{\leq w_k}) \\
&= |\mathcal{E}| - \text{def}(G_{\leq w_k}) \\
&= |\mathcal{E}| - \underbrace{\text{def}(G_{\leq w_1}) + \text{def}(G_{\leq w_1}) - \text{def}(G_{\leq w_2}) + \text{def}(G_{\leq w_2}) \dots + \text{def}(G_{\leq w_{k-1}})}_{=0} - \text{def}(G_{\leq w_k}) \\
&= \sum_{i=1}^k a_{w_i}
\end{aligned}$$

which is a contradiction. \square

This lower bound is minimized in the objective of the Stage I model. Hence, any lower bound on the Stage I model is a lower bound on the overall problem. Additional notation is needed for stating the extended Stage I model.

The neighbors of event-nodes $S \subseteq \mathcal{E}$ in graph $G_{t,\leq w}$ is denoted $\Gamma_{t,\leq w}(S)$ for timeslot t and weight w . Let the variable $\text{def}_{t,\leq w} \in \mathbb{N}_0$ be the deficiency of subgraph $G_{t,\leq w}$. The deficiencies for each subgraph can be determined by adding the following constraint (follows directly from Theorem 4.1 and the definition of the deficiency for a bipartite graph),

$$\sum_{e \in S} y_{e,t} - \text{def}_{t,\leq w} \leq |\Gamma_{t,\leq w}(S)| \quad \forall S \subseteq \mathcal{E}, t \in \mathcal{T}, w \in \mathcal{W} \quad (15)$$

Model (16) shows the extended model. Variables $\text{def}_{t,\leq w}$ and $a_{t,w}$ are specified to be continuous as they will naturally take integer values. Obviously an exponential amount of constraints is added due to (16d), but it will be shown that for our practical purpose, the amount of required constraints is low.

Stage I extended with Hall's condition (16)

$$\min \quad w^I = \sum_{e \in \mathcal{E}, t \in \mathcal{T}} \phi_{e,t} y_{e,t} + \sum_{t \in \mathcal{T}, w \in \mathcal{W}} w a_{t,w} \quad (16a)$$

s.t.

$$\text{(one timeslot)} \quad \sum_{t \in \mathcal{T}} y_{e,t} = 1 \quad \forall e \in \mathcal{E} \quad (16b)$$

$$\text{(resource conf.)} \quad \sum_{e \in E'_a} y_{e,t} \leq 1 \quad \forall a \in \mathcal{A}, t \in \mathcal{T} \setminus t_D \quad (16c)$$

$$\text{(Hall's)} \quad \sum_{e \in S} y_{e,t} - \text{def}_{t,\leq w} \leq |\Gamma_{t,\leq w}(S)| \quad \forall S \subseteq \mathcal{E}, t \in \mathcal{T}, w \in \mathcal{W} \quad (16d)$$

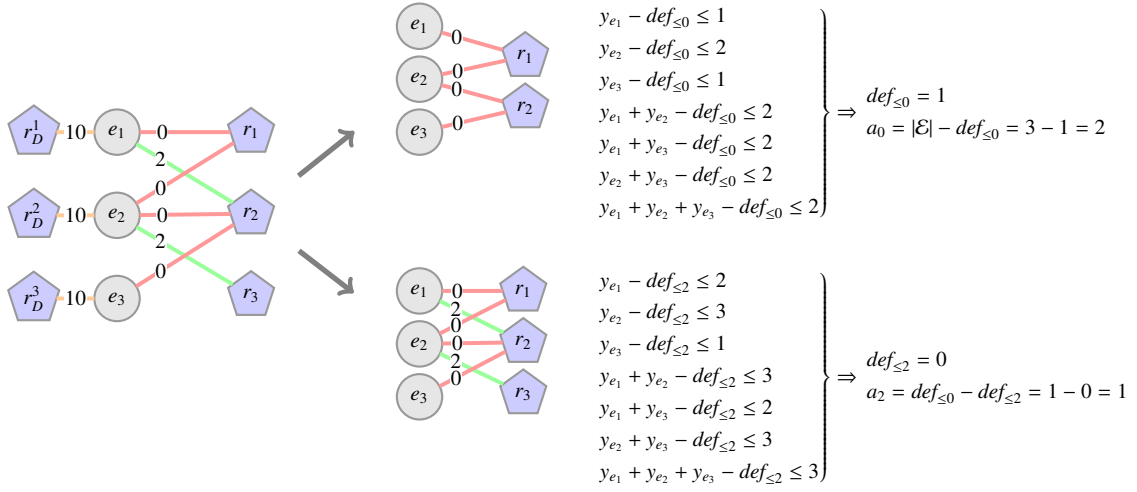
$$\text{(LB)} \quad |\mathcal{E}| - \text{def}_{t,\leq w_1} = a_{t,w_1} \quad \forall t \in \mathcal{T} \quad (16e)$$

$$\text{(LB)} \quad \text{def}_{t,\leq w_{-1}} - \text{def}_{t,\leq w} = a_{t,w} \quad \forall t \in \mathcal{T}, w \in \mathcal{W}, \text{ord}(w) > 1 \quad (16f)$$

$$y_{e,t} \in \{0, 1\} \quad (16g)$$

$$\text{def}_{t,\leq w}, a_{t,w} \in \mathbb{R}^+ \quad (16h)$$

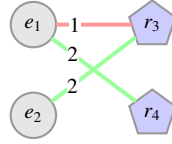
Example 4.1. Below is shown an example of a bipartite graph and its subgraphs for some timeslot. Three different room-weights exists, $\mathcal{W} = \{0, 2, 10\}$. Clearly, an optimal solution to the matching problem of this graph is $(e_1, r_1), (e_2, r_3), (e_3, r_2)$ with value 2. The subgraphs for weights 0 and 2 are shown, and the lower bound derived.



Hence the lower bound is derived as:

$$LB = a_0 0 + a_2 2 = 2$$

Example 4.2. Naturally, the lower bound is not necessarily tight, as shown by the following small example.



For weight $w_1 = 1$ the deficiency of G_1 is $\text{def}(G_1) = 1$ and therefore $a_1 = 1$. As the deficiency for G_2 is $\text{def}(G_2) = 0$ we also have $a_2 = 1$. The lower bound therefore reads $1 \cdot 1 + 2 \cdot 1 = 3$. But obviously the only (and therefore minimal weight) maximum matching has weight 4. In fact, by increasing the weight on the weight 2 edges, it is seen that the gap between the lower bound and the actual minimal weight maximum matching could potentially be arbitrarily large. For the practical problem handled later, the weights can take values $\{1, 2, \dots, 10\}$, and therefore the gap between weights is low. The gap between the lower bound and the actual matchings obtained will be investigated experimentally.

4.2. An exact approach using Egerváry's theorem

An alternative approach to the derived lower bound, the theorem of Egerváry (Egerváry (1931)) can be used to characterize the minimum weight of a matching in a bipartite graph, which deserves a mentioning in this context. The theorem states the following ((Schrijver, 2003, Theorem 17.1), here stated as a minimum weight problem):

Theorem 4.3. Let $G = (V, E)$ be a bipartite graph and let $w : E \rightarrow \mathbb{R}^+$ be a weight function. Then the minimum weight of a matching in G is equal to the maximum value of $y(V)$, where $y : V \rightarrow \mathbb{R}^+$ is such that

$$y_u + y_v \leq w_e \quad \forall u, v \in V, (u, v) \in E$$

However, since we consider a bipartite graph for each timeslot, and each bipartite graph in worst case has $|\mathcal{E}| |\mathcal{R}|$ vertices (which occurs often in practice), the amount of required constraints is of magnitude $|\mathcal{E}| |\mathcal{R}| |\mathcal{T}|$, so this is not a tractable approach. Furthermore, since the graph is not static (i.e. its structure depends on assignments of events to timeslots), a min – max formulation would be required.

4.3. Generating Hall's inequalities

To generate the Hall's inequalities, it is necessary to exploit the structure of the underlying graph. I.e. we use problem specific knowledge to overcome the requirement of enumerating all subsets of events. In the Lectio case, two important features are known about the bipartite graphs:

- An event often has a special association with one specific room. This is either because the event is locked to that room, or because a penalty is imposed on *not* assigning an event to the room it was previously assigned to. In the later case, this means that one room has a lower weight than all other rooms for the particular event. Hence, in the subgraph $G_{\leq w}$ for this respective lower weight, only a single edge exists for the event. An event with only a single adjacent edge is denoted as a *singleton* event from now on.
- Furthermore, predefined feature-groups of rooms exist. A feature group of rooms is devoted to a certain type of lecture, for instance chemistry or physics, which require a room with specialized equipment. Hence many events are adjacent to the exact same set of rooms.

These graphs are hence exploited by separately considering the inequalities induced by singleton events and the inequalities induced by all other events, and finally those inequalities induced by combining these. The approach is formalized below. It should be remarked that applying this type of decomposition will require exploiting at least some properties of the underlying graph. We refer to Balas and Pulleyblank (1983), Edmonds (1965) and Lach and Lübbecke (2008) as helpful resources in this aspect.

For a subset of rooms $R \subseteq \mathcal{R}$, let $\Gamma^{-1}(R)$ be the set of events adjacent to *only* rooms in R , i.e. $\Gamma^{-1}(R) = \{e \in \mathcal{E} \mid \Gamma(\{e\}) \subseteq R\}$.

Theorem 4.4. *The Hall inequalities*

$$\sum_{e \in S} y_e - \text{def} \leq |\Gamma(S)| \quad \forall S \subseteq \mathcal{E}$$

are fully contained in

$$\sum_{e \in \Gamma^{-1}(R)} y_e - \text{def} \leq |R| \quad \forall R \subseteq \mathcal{R}$$

Proof. Let $S \subseteq \mathcal{E}$ be any set of events. Now we let $R = \Gamma(S)$. Obviously we have $S \subseteq \Gamma^{-1}(R) = \Gamma^{-1}(\Gamma(S))$. If $\sum_{e \in \Gamma^{-1}(R)} y_e - \text{def} \leq |R|$ holds we get

$$\sum_{e \in S} y_e - \text{def} \leq \sum_{e \in \Gamma^{-1}(R)} y_e - \text{def} \leq |R| = |\Gamma(S)| \quad \square$$

This means that instead of having a constraint for every subset of events we can do with a constraint for every subset of rooms (which are considerably less).

Next we can further reduce the number of necessary constraints by exploiting symmetry between rooms. Rooms which are adjacent to exactly the same events can be grouped, and essentially treated as one room.

Theorem 4.5. *Let $R_1, \dots, R_m \subseteq \mathcal{R}$ be distinct ($i \neq j \Rightarrow R_i \cap R_j = \emptyset$) subsets of rooms. Let $I \subseteq \{1, \dots, m\}$ be an index set such that*

$$\bigcup_{i \in I} \Gamma^{-1}(R_i) = \Gamma^{-1}\left(\bigcup_{i \in I} R_i\right) \quad (\text{i.e. there is no event that only fits into a combination of the room sets in } I)$$

Then the Hall constraint

$$\sum_{e \in \Gamma^{-1}(\bigcup_{i \in I} R_i)} y_e - \text{def} \leq \left| \bigcup_{i \in I} R_i \right|$$

is dominated by

$$\begin{aligned} \sum_{e \in R_i} y_e - \text{def}_i &\leq |R_i| \quad \forall i \in I \\ \sum_{i \in I} \text{def}_i &\leq \text{def} \end{aligned}$$

where $\text{def}_i \in \mathbb{N}_0$ is the deficiency of index $i \in I$, i.e. $\text{def}_i = \text{def}(\Gamma^{-1}(R_i))$.

Proof. First note that $\sum_{i \in I} \text{def}_i \leq \text{def}$ implies

$$\sum_{e \in \Gamma^{-1}(\bigcup_{i \in I} R_i)} y_e - \text{def} \leq \sum_{i \in I} \sum_{e \in \Gamma^{-1}(R_i)} y_e - \text{def}_i$$

Next by $\sum_{e \in \Gamma^{-1}(R_i)} y_e - \text{def}_i \leq |R_i|$ we get

$$\sum_{i \in I} \sum_{e \in \Gamma^{-1}(R_i)} y_e - \text{def}_i \leq \sum_{i \in I} |R_i| = \left| \bigcup_{i \in I} R_i \right|$$

where the later equality holds as the R_i are distinct. \square

Since the amount of possible ways to select I is exponential, this shows a potential way to limit the amount of necessary inequalities.

The graphs of the Lectio instances usually have the following structure, as previously discussed: Certain events are fixed to a specific room. These events are known as singleton events, and are denoted with the set E^1 . If the singleton events are discarded, all other rooms can be grouped into groups $\mathcal{I} = \{1, 2, \dots, m\}$, i.e. $R_i \subseteq \mathcal{R} \forall i \in \mathcal{I}$, where every room is connected to the very same events as the other rooms of the same group. In particular this means

$$\Gamma^{-1}(R) \setminus E^1 = \emptyset \quad \forall R \subsetneq R_i, i \in \mathcal{I} \quad (17)$$

I.e. no event is adjacent to only a subset of rooms of the room-groups, except for the singleton events. The key observation here is that the number of these groups of rooms is low, yielding a tractable way to generate the Hall inequalities. By Theorem 4.4 we know that a subset of rooms fully characterises one of the Hall constraints (and that it is sufficient to consider only those).

Corollary 4.1. *Given the structure of the Lectio graphs, only the following subsets of rooms need to be considered wrt. eq. (15) (in the altered form defined by Theorem 4.4):*

$$(I) \quad \Gamma(e) \quad \forall e \in E^1 \quad (18)$$

$$(II) \quad \bigcup_{i \in I} R_i \quad \forall I \subseteq \mathcal{I} \quad (19)$$

Proof. For contradiction, let $\tilde{R} \subseteq \mathcal{R}$ be any other subset of rooms, i.e.

$$\begin{aligned} \tilde{R} &\neq \Gamma(e) \quad \forall e \in E^1 \\ \tilde{R} &\neq \bigcup_{i \in I} R_i \quad \forall I \subseteq \mathcal{I} \end{aligned}$$

\tilde{R} can be decomposed into subsets $\tilde{R}_i, i \in \mathcal{I}$, such that $\tilde{R}_1 \subseteq R_1, \tilde{R}_2 \subseteq R_2, \dots, \tilde{R}_m \subseteq R_m$ and $\bigcup_{i \in \mathcal{I}} \tilde{R}_i = \tilde{R}$.

For each of the decomposed room sets \tilde{R}_i we can now have one of the three following cases (by eq. (17), which disallows that $\tilde{R}_i \neq R_i$ and $\Gamma^{-1}(\tilde{R}_i) \setminus E^1 \neq \emptyset$):

1. $\tilde{R}_i = R_i$
2. $\tilde{R}_i \neq R_i$ and $\Gamma^{-1}(\tilde{R}_i) \cap E^1 \neq \emptyset$

$$3. \tilde{R}_i \neq R_i \text{ and } \Gamma^{-1}(\tilde{R}_i) = \emptyset$$

Let the respective indices be contained in the sets I_1, I_2 and I_3 . The rooms from the third case ($\tilde{R}_i, i \in I_3$) do not add events to the left hand side of a Hall constraint and can therefore be ignored.

If combining the rooms from the first case to $R' = \bigcup_{i \in I_1} \tilde{R}_i$ we get one of the already considered combinations of room groups. Now note that there is no event fitting into the combination of R' with any of the rooms from the second case (their Γ^{-1} only contains singleton events) and therefore the condition for Theorem 4.5 is met:

$$\left(\bigcup_{i \in I_2} \Gamma^{-1}(\tilde{R}_i) \right) \cup \Gamma^{-1}(R') = \Gamma^{-1} \left(\left(\bigcup_{i \in I_2} \tilde{R}_i \right) \cup R' \right)$$

So we now know that the Hall constraint corresponding to \tilde{R} is unnecessary. \square

Algorithm (4.1) shows the implemented algorithm for generation all necessary Hall constraints according to this construction.

Algorithm 4.1 Generating Hall's conditions

- 1: **input:** bipartite graph $G = (\mathcal{E} \cup \tilde{\mathcal{R}}, E)$
 - 2: **output:** set of sets of rooms H , which each constitute a Hall inequality
 - 3: identify E^1 of G
 - 4: $N_r = \{e \in \mathcal{E} \setminus E^1 \mid r \in \Gamma(e) \neq \emptyset\}$ ▷ Identity adjacent events for each room
 - 5: $T = \{R \subseteq \tilde{\mathcal{R}} \mid (r_i, r_j) \in R, i \neq j, N_{r_i} = N_{r_j}\}$ ▷ Groups of rooms which are adjacent to the same events
 - 6: **for all** $S \in \mathcal{P}(T)$ **do** ▷ $\mathcal{P}(T)$ denotes the powerset of T , i.e. the collection of all subsets
 - 7: $H = H \cup \{r \in R \mid R \in S\}$ ▷ Add set of room (eq. (19))
 - 8: **end for**
 - 9: $H = H \cup \{r\} \quad \forall r \in \Gamma(E^1)$ ▷ Add rooms of singleton events (eq. (18))
-

In Line 5 rooms are grouped. Here it should be remarked that this is done in a way that identifies the minimum number of groups of rooms. The amount of generated inequalities is hence exponential in the number of groups of rooms. For the Lectio high school timetabling problem, this number is in general low. However, an artificial limit of a maximum of 12 different groups of rooms is imposed, allowing in magnitude of 2^{12} inequalities to be generated for each timeslot. In practice, only two problem instances are restricted by this limit ("HasserG2012" and "SlagelG2012"). The room groups to generate inequalities are selected by ordering the room groups in terms of total number of adjacent events to all other room groups, and taking those room groups where this number is highest. Obviously, omitting some inequalities will not change the fact that the room allocation penalty added to Stage I is a lower bound on the objective of Stage II.

5. Lectio High School Timetabling Problem

To establish computational results, Stage I and Stage II are extended to the full version of the Danish case of high school timetabling described in Sørensen and Stidsen (2013). This variant of the problem is used in the timetabling component of the high school ERP-system Lectio, and hence reflects all aspects of a practical timetabling optimization problem. Lectio Timetabling is used by many high schools in Denmark, and this formulation of the problem has been used in production mode for over a year. In this paper a brief introduction to each of the added constraints and variables is given. More in-depth description and motivation can be found in Sørensen and Stidsen (2013).

This timetabling problem contains more types of constraints than what is usually found in the literature. This is mainly related to the big number of different high schools which use it, which inevitably gives a big variety of required features. However, a conversion scheme from this timetabling problem to the general XHSTT format is known, so the Lectio problem fits within the general concepts of high school timetabling problems.

Extensive computational experiments have shown that the usual formulation of this timetabling problem using a binary variable with three indices is very challenging for the commercial MIP solver Gurobi 5, which is among

the very best general-purpose MIP solvers according to recent benchmarks of Mittelman (2013). Therefore this timetabling problem is a good candidate for testing the TSD approach.

5.1. Stage I

The set of timeslots \mathcal{T} is defined by the combination of the set of days \mathcal{D} , and the set of daily-timeslots (known as *modules*) \mathcal{M} . The set of resources \mathcal{A} consists of teachers and students, which is also known as the set of *entities*. Furthermore, the set of *classes* is denoted \mathcal{C} . A class $c \in \mathcal{C}$ is a *non-physical* resource treating a specific teaching-subject, and is associated with a certain set of events. Hence, an event can be viewed as a single lecture of a certain class. Parameter $J_{e,c} \in \{0, 1\}$ takes value 1 if event $e \in \mathcal{E}$ is part of class $c \in \mathcal{C}$, and 0 otherwise.

Variable $v_{a,t} \in \{0, 1\}$ takes value 1 if entity $a \in \mathcal{A}$ is active in timeslot $t \in \mathcal{T}$, and 0 otherwise. Variable $f_{a,d} \in \{0, 1\}$ takes value 1 if entity $a \in \mathcal{A}$ has no events scheduled on events on day $d \in \mathcal{D}$ (we say that the entity has a *day off*, even though he/she might be occupied by unscheduled activities, such as lecture preparation), and 0 otherwise. Variable $b_{c,t} \in \{0, 1\}$ takes value 1 if class $c \in \mathcal{C}$ has at least one lecture in timeslot $t \in \mathcal{T}$, and 0 otherwise. Variable $n_{c,d} \in \{0, 1\}$ takes value if class $c \in \mathcal{C}$ has a neighbor-day conflict on day $d \in \mathcal{D}$. A neighbor-day conflict occurs when the same class has scheduled events on two consecutive days. Variable $o_{a,d} \in \{0, 1\}$ takes value 1 if entity $a \in \mathcal{A}$ has only one event on day $d \in \mathcal{D}$, and 0 otherwise. Days with only one lecture are undesirable and should be avoided. Variable $w_c \in \mathbb{N}_0$ is the amount which class $c \in \mathcal{C}$ is 'out of week-balance'. I.e. if the set of timeslots is made up of times from more than one week, the amount of events of each class in each week must be equivalent (as far as possible). Variable $h_{a,d} \in \mathbb{N}_0$ is the amount of idle timeslots (a timeslot with no activity, but there exists both at least one earlier and one later timeslot with activity) for entity $a \in \mathcal{A}$ on day $d \in \mathcal{D}$. Variables $\bar{h}_{a,d} \in \mathbb{N}_0$ denote the ordinal number of the first and last timeslot with activity on day $d \in \mathcal{D}$ for entity $a \in \mathcal{A}$, respectively.

The objective consists of 6 additional terms. These denote the weighted sum of entity idle slots (weight $\phi_a \in \mathbb{R}^+$), neighbor-day conflicts (weight $\zeta \in \mathbb{R}^+$), days with only one lecture (weight $\eta_a \in \mathbb{R}^+$), days-off for teachers (weight $\gamma_a \in \mathbb{R}^+$), days-off for students (weight $\delta_a \in \mathbb{R}^+$), and class week stability (weight $\iota \in \mathbb{R}^+$), respectively.

Let parameters S_e and C_e be the set of events which should be scheduled in the same timeslot as event $e \in \mathcal{E}$, and in the timeslot immediately following event $e \in \mathcal{E}$, respectively. Parameter $P_{d,d'} \in \{0, 1\}$ takes value 1 if day $d \in \mathcal{D}$ and day $d' \in \mathcal{D}$ are neighbor-days, and 0 otherwise. Parameter $R_{c,d} \in \{0, 1\}$ takes value 1 if class $c \in \mathcal{C}$ is part of some event which is locked to some timeslot on day $d \in \mathcal{D}$, and let $N_c \in \mathbb{N}_0$ be the number of allowed neighbor-day conflicts for class $c \in \mathcal{C}$. \mathcal{T}_d denotes the set of timeslots on day $d \in \mathcal{D}$. Parameter $D_{e,t} \in \{0, 1\}$ takes value 1 if event $e \in \mathcal{E}$ can be scheduled in timeslot $t \in \mathcal{T}$, and 0 otherwise. Parameter $F_a \in \mathbb{N}_0$ denotes the amount of required days off for entity $a \in \mathcal{A}$. Parameter $W_a \in \mathbb{N}_0$ denotes the maximum amount of events which can be scheduled to entity $a \in \mathcal{A}$ on any given day.

A class can only have one event assigned to each day, unless it is specified that multiple events should be placed in contiguous positions. We say that such *day-conflicts* are infeasible. The set $E''' \subseteq \mathcal{E}$ denotes the set of events for which day-conflicts are checked.

The most common case is that a school creates a timetable for a single week. However, some schools desire to create a two-week timetable instead. This allows more flexibility in the planning; take for instance a class with a nominated teaching load of three events per week. In case the school uses a two-week timetable, this class can for instance have one double lecture in the first week, and two double lectures in the second week. $d(\underline{\mathcal{T}})$ and $d(\overline{\mathcal{T}})$ denotes the set of days in the first and in the second week, respectively. $\underline{\mathcal{T}}$ and $\overline{\mathcal{T}}$ denotes the timeslots in the first and second week, respectively.

The complete Stage I model is shown in (20).

Stage I Lectio

$$\begin{aligned}
 \min \quad & w^I = \sum_{e \in \mathcal{E}, t \in \mathcal{T}} \phi_{e,t} y_{e,t} + \sum_{t \in \mathcal{T}, w \in \mathcal{W}} w a_{t,w} + \sum_{a \in \mathcal{A}, d \in \mathcal{D}} \beta_a h_{a,d} + \zeta \sum_{c \in \mathcal{C}, d \in \mathcal{D}} n_{c,d} + \sum_{a \in \mathcal{A}, d \in \mathcal{D}} \eta_a o_{a,d} \\
 \text{s.t.} \quad & + \sum_{a \in \mathcal{A}} \gamma_a \left[|\mathcal{D}| - \sum_{d \in \mathcal{D}} f_{a,d} \right] + \sum_{a \in \mathcal{A}, d \in \mathcal{D}} \delta_a f_{a,d} + \iota \sum_{c \in \mathcal{C}} w_c \\
 \text{(one timeslot)} \quad & \sum_{t \in \mathcal{T}} y_{e,t} = 1 \quad \forall e \in \mathcal{E} \\
 \text{(entity time aux.)} \quad & \sum_{e \in E_a} y_{e,t} = v_{a,t} \quad \forall a \in \mathcal{A}, t \in \mathcal{T} \\
 \text{(entity conf.)} \quad & \sum_{t \in \mathcal{T}_d} v_{a,t} + f_{a,d} \leq 1 \quad \forall a \in \mathcal{A}, d \in \mathcal{D} \\
 \text{(Hall's)} \quad & \sum_{e \in S} y_{e,t} - \text{def}_{t, \leq w} \leq |\Gamma_{t, \leq w}(S)| \quad \forall S \subseteq \mathcal{E}, t \in \mathcal{T}, w \in \mathcal{W} \\
 \text{(room alloc. lb)} \quad & |\mathcal{E}| - \text{def}_{t, \leq w_1} = a_{t, w_1} \quad \forall t \in \mathcal{T} \\
 \text{(room alloc. lb)} \quad & \text{def}_{t, \leq w-1} - \text{def}_{t, \leq w} = a_{t, w} \quad \forall t \in \mathcal{T}, w \in \mathcal{W}, \text{ord}(w) > 1 \\
 \text{(locked time)} \quad & y_{e,t} = 1 \quad \forall e \in \mathcal{E}, t \in \mathcal{T}, LT_{e,t} = 1 \\
 \text{(same time)} \quad & y_{e,t} - y_{e',t} = 0 \quad \forall e \in \mathcal{E}, e' \in S_e, t \in \mathcal{T} \\
 \text{(cont. times)} \quad & y_{e,t} - y_{e',t'} = 0 \quad \forall e \in \mathcal{E}, e' \in C_e, (t, t') \in \mathcal{T}, d_t = d_{t'}, \\
 & \quad \text{ord}(t) + 1 = \text{ord}(t') \\
 \text{(n.d. conf.)} \quad & \sum_{t \in \mathcal{T}_d} b_{c,t} + \sum_{t \in \mathcal{T}_{d'}} b_{c,t} - n_{c,d} \leq 1 \quad \forall c \in \mathcal{C}, (d, d') \in \mathcal{D}, P_{d,d'} = 1, \\
 & \quad R_{c,d} + R_{c,d'} \leq 1 \\
 \text{(n.d. conf.)} \quad & \sum_{d \in \mathcal{D}} n_{c,d} \leq N_c \quad \forall c \in \mathcal{C} \\
 \text{(forbid. times)} \quad & \sum_{t \in \mathcal{T}, D_{e,t}=0} y_{e,t} = 0 \quad \forall e \in \mathcal{E} \\
 \text{(idle slots)} \quad & \bar{h}_{a,d} - \underline{h}_{a,d} - \sum_{t \in \mathcal{T}_d} v_{a,t} + 1 = h_{a,d} \quad \forall a \in \mathcal{A}, d \in \mathcal{D} \\
 \text{(idle slots)} \quad & |\mathcal{M}| - (|\mathcal{M}| - \text{ord}(t)) v_{a,t} \geq \underline{h}_{a,d} \quad \forall a \in \mathcal{A}, d \in \mathcal{D}, t \in \mathcal{T}_d \\
 \text{(idle slots)} \quad & \text{ord}(t) v_{a,t} \leq \bar{h}_{a,d} \quad \forall a \in \mathcal{A}, d \in \mathcal{D}, t \in \mathcal{T}_d \\
 \text{(days off)} \quad & \sum_{d \in \mathcal{D}} f_{a,d} \geq F_a \quad \forall a \in \mathcal{A} \\
 \text{(days off)} \quad & \sum_{t \in \mathcal{T}_d} v_{a,t} + f_{a,d} \geq 1 \quad \forall a \in \mathcal{A}, d \in \mathcal{D} \\
 \text{(day conf.)} \quad & \sum_{e \in E'''} J_{e,c} y_{e,t} \leq b_{c,t} \quad \forall c \in \mathcal{C}, t \in \mathcal{T} \\
 \text{(day conf.)} \quad & \sum_{t \in \mathcal{T}_d} b_{c,t} \leq 1 \quad \forall c \in \mathcal{C}, d \in \mathcal{D} \\
 \text{(work limit)} \quad & \sum_{e \in \mathcal{E}, t \in \mathcal{T}_d} y_{e,t} \leq W_a \quad \forall a \in \mathcal{A}, d \in \mathcal{D} \\
 \text{(one lecture)} \quad & 2 - \sum_{t \in \mathcal{T}_d} v_{a,t} - 2f_{a,d} \leq o_{a,d} \quad \forall a \in \mathcal{A}, d \in \mathcal{D} \\
 \text{(class stabl.)} \quad & \left| \sum_{e \in \mathcal{E}, t \in \mathcal{T}} J_{e,c} y_{e,t} - \sum_{e \in \mathcal{E}, t \in \bar{\mathcal{T}}} J_{e,c} y_{e,t} \right| - 1 = w_c \quad \forall c \in \mathcal{C} \\
 \text{(d.o. stabl.)} \quad & \left| \sum_{d \in d(\mathcal{T})} f_{a,d} - \sum_{d \in d(\bar{\mathcal{T}})} f_{a,d} \right| \leq 1 \quad \forall a \in \mathcal{A} \\
 & y_{e,t} \in \{0, 1\} \\
 & v_{a,t}, f_{a,d}, b_{c,t}, n_{c,d}, o_{a,d} \in [0, 1] \\
 & h_{a,d}, \underline{h}_{a,d}, \bar{h}_{a,d}, w_c, \text{def}_{t, \leq w}, a_{t,w} \in \mathbb{R}^+
 \end{aligned}
 \tag{20}$$

Constraint (20c) constraints the auxiliary variable $v_{a,t}$ properly. Constraint (20d) treats entity conflicts in a slightly changed formulation, to also constrain variable $f_{a,d}$ properly. Constraints (20e)-(20g) define the lower bound on room allocation, and are similar to those previously described. Constraint (20h) ensures the assigning of events are locked to a certain timeslot. Constraints (20i) and (20j) ensure the placement of events which must be placed in the same/contiguous timeslots. Constraints (20k) and (20l) ensure that variable $n_{c,d}$ is constrained properly, and that no more than N_c neighbor-day conflicts are scheduled for class $c \in C$. Constraint (20m) poses restrictions on timeslots for which an entity is unavailable. Constraints (20n)-(20p) ensures that idle slots for entities are penalized accordingly. Constraint (20q) ensures that sufficient days off is assigned to each entity. Constraint (20r) makes sure that if an entity $a \in \mathcal{A}$ has no event on some day $d \in \mathcal{D}$, then variable $f_{a,d}$ is forced to take value 1. This is necessary as this variable is minimized in the objective. Constraints (20s) and (20t) ensure that day-conflicts for classes does not occur, and constraints the variable $b_{c,t}$ properly. Constraint (20u) ensures that the limit on the amount of events assigned to a day for entity a is respected. For an entity, days with only one event scheduled are undesirable. Constraint (20v) penalizes days with only one events scheduled for entity a . Constraint (20w) forces week-stability for events of classes, i.e. in case two-weeks are being planned, events for courses must be spread evenly throughout the weeks. Constraint (20x) ensures that in case several weeks are being planned, the days off for an entity are spread evenly throughout the weeks.

5.2. Stage II

Let variable $v_{c,r} \in \{0, 1\}$ take value 1 if there is at least one event of which class $c \in C$ participates assigned to room $r \in \mathcal{R}$, and 0 otherwise. Variable $s_c \in \mathbb{N}_0$ is the amount of 'excess' rooms assigned to events of class $c \in C$, i.e. the total amount of rooms assigned minus one. This is used to enforce room stability for classes, since it is undesirable for a class to be assigned too many different rooms. Parameter $LR_{e,r} \in \{0, 1\}$ takes value 1 if event $e \in \mathcal{E}$ is locked room $r \in \mathcal{R}$.

Stage II Lectio (21)

$$\min \quad w^{II} = \sum_{e \in \mathcal{E}, r \in \mathcal{R}} \pi_{e,r} z_{e,r} + \epsilon \sum_c s_c \quad (21a)$$

s.t.

$$\text{(one room)} \quad \sum_{r \in \mathcal{R}} z_{e,r} = 1 \quad \forall e \in \mathcal{E} \quad (21b)$$

$$\text{(room conf.)} \quad \sum_{e \in \mathcal{E}} y_{e,t}^* z_{e,r} \leq G_{r,t} \quad \forall r \in \mathcal{R} \setminus r_D, t \in \mathcal{T} \setminus t_D \quad (21c)$$

$$\text{(eligible rooms)} \quad z_{e,r} \leq K_{e,r} \quad \forall e \in \mathcal{E}, r \in \mathcal{R} \quad (21d)$$

$$\text{(locked rooms)} \quad z_{e,r} = 1 \quad \forall e \in \mathcal{E}, r \in \mathcal{R}, LR_{e,r} = 1 \quad (21e)$$

$$\text{(room stbl.)} \quad \sum_{e \in \mathcal{E}, t \in \mathcal{T} \setminus t_D} J_{e,c} y_{e,t}^* z_{e,r} - \sum_{e \in \mathcal{E}} J_{e,c} v_{c,r} \leq 0 \quad \forall r \in \mathcal{R} \setminus r_D, c \in C \quad (21f)$$

$$\text{(room stbl.)} \quad \sum_{r \in \mathcal{R}} v_{c,r} - 1 \leq s_c \quad \forall c \in C \quad (21g)$$

$$\text{(not only room)} \quad \sum_{r \in \mathcal{R} \setminus r_D} y_{e,t_D}^* z_{e,r} - \sum_{r \in \mathcal{R}} LR_{e,r} \leq 0 \quad \forall e \in \mathcal{E} \quad (21h)$$

$$z_{e,r}, v_{c,r} \in \{0, 1\} \quad (21i)$$

$$s_c \in \mathbb{R}^+ \quad (21j)$$

Constraint (21e) ensures that events with locked rooms are assigned accordingly. Constraints (21f) and (21g) constraints variables $v_{c,r}$ and s_c properly, and thereby penalizes room stability. Constraint (21h) enforces that an event cannot be assigned a room if it not assigned to a timeslot, unless the event is locked to a specific room.

Notice that the room stability constraints (21f) and (21g) of Model (21) are not handled in any way in the Stage I model. Additional constraints which handle these constraints would theoretically improve the decomposition. It is however not trivial to model these constraints as a matching problem in a bipartite graph, so another approach may be required. This is a subject for future research. Apart from the room stability constraints, all other constraints are

optimally handled by the decomposition, with the exception of the room allocation penalties, which are only partially integrated in the Stage I model.

6. Computational Results

For implementation purposes, Gurobi 5.0.1 was used as MIP solver on a machine with an Intel Core i7 930@2.80GHz CPU and 12GB of RAM, running Windows 8 64bit. Default parameter settings were used, and the interface was C# 4.5. The problem instances have been taken directly from the Lectio database, and are the same ones used in Sørensen and Stidsen (2013). These 100 real-world datasets provide a substantial ground for concluding on the numerical experiments. Note that 3 of these instances are available in the XHSTT format (Post et al. (2012a)) at <http://www.utwente.nl/ctit/hstt/>. We plan to make additional datasets available in this format in the future.

A time limit of 7200 seconds was imposed (6480 seconds for Stage I, and 720 seconds for Stage II), and Gurobi was allowed to use 8 threads. For the Stage I model, the initial solution given to Gurobi consists of assigning all events to the dummy-timeslot, except for those events locked to a specific timeslot. The initial solution for the Stage II model is analogous; Events are assigned to the dummy-room or the room which the event is locked too. A single run was used to establish results, as Gurobi has deterministic behavior.

Two other solution approaches are described for the same timetabling problem in Sørensen and Stidsen (2013). These are used in comparison with the algorithm of this paper, and are briefly described below:

- The 'usual' formulation using a three-index binary variable, denoted *3-index model* in the following. This is solved using Gurobi with standard settings, with a time limit of 7200 seconds. The objectives listed are the result of a single run.
- An *Adaptive Large Neighborhood Search* heuristic, denoted *ALNS* in the following. The reported objectives for this method is the average obtained over 10 runs, each run with a timelimit of 240 seconds. Hence, the comparison of objectives wrt. this heuristic is not 'fair', but it will be seen that even with this shorter timelimit, the ALNS in general performs best. This method is the one currently used by the customers of Lectio.

Furthermore, we test the described decomposition both with and without the room penalties added to the Stage 1 model (i.e. Model (20) with and without equations (20e), (20f) and (20g)). Thereby an empirical test of the effect of extending Stage I is performed. In the following, these two methods are denoted *TSD* and *TSD^{RoomLB}*, respectively. Notice that the results for TSD can also be found in the technical report Sørensen and Stidsen (2013).

Table 1 shows the obtained results. Table 2 summarizes some key numbers. Table 3 gives a summary for the three exact methods. A gap between an IP objective z and a lower bound LB is calculated by $100 \frac{z-LB}{z}$.

Table 1: *Computational results. For each dataset is shown the objective 'Obj' obtained by each method. For the IP-based approaches, also the best found lower bounds 'LB' are shown (i.e. for the 3-index model is shown the final value of the LP-relaxation used internally by Gurobi, and for TSD is shown the final value of the LP-relaxation of the Stage I model, as described in Section 4). If a solution is best overall, it is marked in **bold**. If a bound is best overall, it is marked with a '*'. For the two-stage approach of this paper is shown the runtime 'Time' and final gap 'Gap' found by Gurobi for both Stage I and Stage II. For Stage II, column 'Diff.' denotes the difference between the lower bound for room allocation of Stage I, and the actual matching obtained by Stage II (excluding room stability). Column 'Gap' denotes the best overall gap, i.e. the gap between the best available solution and the best available bound.*

Dataset	Previous methods						TSD ^{RoomLB}						
	ALNS	3-index model		TSD		Stage I		Stage II			Obj	LB	Gap
	Obj	Obj	LB	Obj	LB	Time	Gap	Time	Gap	Diff.			
AalborgTG2012	6317	6118	*5946	6018	5934	>6480	0.7	4	0.0	0	6005	5941	1.0
AarhusA2011	10037	58015	-	15872	*5986	>6480	66.6	154	0.0	160	18122	5985	40.4
AarhusA2012	7971	17096	5722	8947	*6005	>6480	49.4	108	0.0	48	11936	5962	24.7
Aars2009	14900	49504	-	20780	11874	>6480	47.9	14	0.0	0	24240	*12641	15.2
Aars2010	16268	81970	-	25057	13134	>6480	42.7	22	0.0	1	24692	*14151	13.0
Aars2011	14256	77967	-	30623	9709	>6480	68.9	10	0.0	3	33790	*10501	26.3

Continued on next page

Table 1 – continued from previous page

Dataset	Previous methods					TSD ^{RoomLB}							
	ALNS	3-index model		TSD		Stage I		Stage II			Obj	LB	Gap
	Obj	Obj	LB	Obj	LB	Time	Gap	Time	Gap	Diff.			
Aars2012	10701	55049	-	21206	7456	>6480	60.3	21	0.0	1	20274	*8044	24.8
Alssund2010	9967	52717	-	23173	6811	>6480	67.9	324	0.0	8	21455	*6876	31.0
Alssund2012	29803	108810	-	108810	-	>6480	-	6	0.0	0	108810	-	-
BagsvaG2010	3960	6777	3171	3916	3063	>6480	19.4	14	0.0	9	4051	*3227	17.6
BirkerG2011	42063	119600	-	119600	-	>6480	-	7	0.0	0	119600	-	-
BirkerG2012	19552	110180	-	19322	15662	>6480	0.9	>720	1.0	16	18182	*17709	2.6
BjerrG2009	16877	52639	-	35514	11094	>6480	55.2	11	0.0	0	27396	*12288	27.2
BjerrG2010	4983	12868	*3928	5788	3868	>6480	33.1	13	0.0	37	5977	3925	21.2
BjerrG2011	6334	13009	*4142	9302	4060	>6480	64.8	97	0.0	20	11676	4079	34.6
BjerrG2012	8023	17200	*5055	15265	5007	>6480	71.2	160	0.0	16	17404	4991	37.0
BroendG2012	2040	2005	*1881	1929	1859	1028	0.0	17	0.0	5	1928	1877	2.4
CPHWGym2010	6775	34415	-	19363	*3759	>6480	77.4	11	0.0	0	16589	3752	44.5
CPHWGym2011	5679	38232	-	16212	4095	>6480	72.7	10	0.0	0	15046	*4103	27.8
CPHWGym2012	6762	40945	-	15543	4205	>6480	75.5	19	0.0	1	17194	*4215	37.7
CPHWHG2012	11077	46625	8157	23088	*8338	>6480	64.1	16	0.0	0	23219	8326	24.7
CPHWHTX2010	11342	27174	9179	15943	8828	>6480	52.1	7	0.0	0	19314	*9259	18.4
CPHWHTX2011	20734	22466	20460	20708	18490	>6480	0.6	6	0.0	11	20632	*20470	0.8
CPHWHTX2012	16256	25998	14481	21392	13115	>6480	35.4	4	0.0	0	22481	*14531	10.6
DetFG2012	7560	8017	*7168	7265	7018	>6480	0.7	8	0.0	68	7258	7116	1.2
DetKG2010	2947	6058	1732	4006	*1821	>6480	55.6	3	0.0	4	4102	1814	38.2
DetKG2011	2820	5594	1732	4366	1780	>6480	60.9	2	0.0	2	4577	*1781	36.8
EUCN2009	3737	7557	2911	4298	2856	>6480	40.3	4	0.0	0	5001	*2982	20.2
EUCN2010	3882	4231	3329	3463	3246	>6480	1.4	6	0.0	1	3430	*3375	1.6
EUCN2011	1468	1435	*1395	1430	1384	>6480	2.2	1	0.0	2	1426	1384	2.2
EUCN2012	3289	9430	2327	5059	*2363	>6480	60.2	4	0.0	0	5913	2359	28.2
EUCNHG2010	1505	1476	1371	1421	1368	>6480	2.1	2	0.0	0	1408	*1378	2.1
EUCS2012	3714	4689	3576	3783	3347	>6480	3.0	3	0.0	0	3695	*3584	3.0
FaaborgG2008	68124	125330	-	125330	-	>6480	-	14	0.0	0	125330	-	-
FalkonG2009	10449	88890	-	88890	-	>6480	-	5	0.0	0	88890	-	-
FalkonG2011	8584	76170	-	16543	*5183	>6480	75.9	>720	0.0	48	20758	4953	39.6
FalkonG2012	10143	100190	-	16666	*6105	>6480	58.6	>720	0.1	121	14908	6050	39.8
GUAasia2010	6527	6579	6354	6461	6035	26	0.0	>720	0.1	5	6422	*6374	0.7
GUQaqor2011	6674	19623	4537	10005	*4554	>6480	59.9	3	0.0	18	11396	4542	31.8
GUQaqor2012	5733	11488	4314	7619	4294	>6480	55.1	10	0.0	0	9650	*4324	24.6
HadersK2011	7128	51190	-	14229	*3909	>6480	76.2	>720	0.0	43	16494	3888	45.2
HasserG2010	11963	96790	-	96790	-	>6480	-	6	0.0	0	96790	-	-
HasserG2011	16061	99840	-	99840	-	>6480	-	6	0.0	0	99840	-	-
HasserG2012 [†]	18338	112160	-	112034	-	>6480	-	7	0.0	0	112160	-	-
HerningG2010	37	37	*37	37	35	0	0.0	1	0.0	0	37	35	0.0
HerningG2011	15091	163785	-	23117	*9829	>6480	61.8	108	0.0	169	26410	9746	34.9
HerningG2012	13147	185433	-	14952	9763	>6480	48.4	>720	0.1	262	19834	*9817	25.3
HoejeTaG2008	2958	6292	2253	2707	2563	>6480	6.4	3	0.0	0	2775	*2587	4.4
HoejeTaG2009	9157	45260	-	26066	*5773	>6480	79.7	105	0.0	3	27779	5628	37.0
HoejeTaG2010	9862	45095	-	25678	*6188	>6480	78.1	106	0.0	5	27886	6116	37.3
HoejeTaG2011	10158	51050	-	32630	*6726	>6480	78.2	66	0.0	3	30327	6601	33.8
HoejeTaG2012	12502	72455	7592	18627	7845	>6480	79.8	9	0.0	3	39326	*7952	36.4
HorsenS2009	3111	3100	*3100	3100	2865	1	0.0	4	0.0	13	3100	3059	0.0
HorsenS2012	10056	86090	-	86090	-	>6480	-	3	0.0	0	86090	-	-
Johann2012	23001	92575	-	27781	18456	>6480	33.5	233	0.0	6	29491	*19590	14.8
KalundG2011	38479	126150	-	126150	-	>6480	-	9	0.0	0	126150	-	-
KalundG2012	26768	123010	-	123010	-	>6480	-	11	0.0	0	123010	-	-
KalundHG2010	5631	12103	4540	6351	4551	>6480	29.7	6	0.0	0	6605	*4642	17.6
KoebenPG2012	888	1872	637	874	642	>6480	37.9	1	0.0	2	1052	*645	26.2
KoegeH2012	11418	108347	-	20150	9096	>6480	53.7	12	0.0	0	20390	*9440	17.3
KongshoG2010	4296	8889	2411	7954	*2488	>6480	65.9	30	0.0	0	7208	2451	42.1
MariageG2009	8013	54030	-	20138	5118	>6480	69.7	>720	0.0	18	17506	*5286	34.0
MorsoeG2012	5651	42762	-	10241	3854	>6480	66.0	23	0.0	6	11674	*3947	30.2
NaerumG2008	24104	118370	-	117894	-	>6480	-	7	0.0	0	117894	-	-
NaerumG2009	7667	100450	-	6681	*5114	>6480	0.3	>720	6.2	0	5466	5113	6.4

Continued on next page

Table 1 – continued from previous page

Dataset	Previous methods					TSD ^{RoomLB}							
	ALNS	3-index model		TSD		Stage I		Stage II			Obj	LB	Gap
	Obj	Obj	LB	Obj	LB	Time	Gap	Time	Gap	Diff.			
NielsSG2011	4953	10464	3323	6132	*3412	>6480	37.6	9	0.0	0	5397	3367	31.1
NielsSG2012	6952	12747	5722	8003	*5738	>6480	37.6	14	0.0	4	9192	5724	17.5
NordfynG2012	5160	8201	*4152	4890	4048	>6480	23.3	35	0.0	59	5510	4107	15.1
NyborgG2011	13944	94059	-	31809	*6129	>6480	-	7	0.0	4	85816	-	56.0
OdderCFU2010	18219	59540	-	40032	12188	>6480	66.9	66	0.0	2	38875	*12865	29.4
OdderG2009	9308	59851	-	57586	-	>6480	78.1	67	0.0	67	24686	*5361	42.4
OdderG2012	12307	17402	9602	14888	8878	>6480	64.2	4	0.0	57	27199	*9688	21.3
OrdrupG2010	13663	75700	-	12936	10665	>6480	39.5	10	0.0	0	18101	*10810	16.4
OrdrupG2011	21612	116400	-	31329	16904	>6480	38.7	305	0.0	8	28884	*17692	18.1
RibeK2011	21679	61945	-	43175	16209	>6480	53.8	229	0.0	5	39107	*18055	16.7
RysenG2010	39971	110690	-	110690	-	>6480	-	6	0.0	0	110690	-	-
RysenG2011	22260	100313	-	25989	17756	>6480	71.4	9	0.0	5	68927	*19725	11.4
RysenG2012	19841	110111	-	22156	15115	>6480	71.7	14	0.0	15	59124	*16708	15.8
SanktAG2012	4207	4624	3415	3911	3376	>6480	0.7	>720	0.5	39	3721	*3538	4.9
SkanderG2010	7209	7708	6051	6875	5712	>6480	0.6	>720	0.5	72	6485	*6238	3.8
SkanderG2011	22525	88470	-	88470	-	>6480	-	5	0.0	0	88470	-	-
SkanderG2012	20138	98487	-	95319	-	>6480	-	7	0.0	3	95319	-	-
SkiveG2010	43120	194740	-	194740	-	>6480	-	526	0.0	0	194740	-	-
SlagelG2012 [†]	32167	162960	-	162765	-	>6480	-	417	0.0	0	162960	-	-
SoendS2011	11776	83560	-	83560	-	>6480	-	131	0.0	0	83560	-	-
SoendS2012	8420	17778	*6838	11915	6647	>6480	72.5	8	0.0	4	24668	6739	18.8
Struers2012	73361	-	-	207488	-	>6480	-	700	0.0	0	211960	-	-
VardeG2012	10777	20933	*5921	20622	5720	>6480	72.1	12	0.0	2	20496	5668	45.1
VejenG2009	11264	69450	-	69450	-	>6480	73.9	>720	0.0	7	27954	*7290	35.3
Vejlefo2011	13514	52035	-	18043	8511	>6480	60.0	456	0.0	3	22066	*8805	34.8
VestfynG2009	5973	11606	4176	5999	4137	>6480	14.5	553	0.0	18	5032	*4211	16.3
VestfynG2010	6761	16895	*4308	5974	4225	>6480	16.3	65	0.0	21	5239	4290	17.8
VestfynG2011	7013	13624	5110	6657	4925	>6480	19.6	38	0.0	24	6522	*5159	20.9
VestfynG2012	5244	11095	4279	5212	4210	>6480	17.5	149	0.0	21	5319	*4315	17.2
ViborgK2011	14923	99170	-	99170	-	>6480	-	6	0.0	0	99170	-	-
ViborgTG2009	10216	19891	8695	12077	8356	>6480	34.7	45	0.0	3	13387	*8740	14.4
ViborgTG2010	4932	12727	4130	10226	3990	>6480	60.9	11	0.0	19	10665	*4146	15.9
ViborgTG2011	7478	16433	6716	9808	6204	>6480	38.8	12	0.0	13	11088	*6772	9.4
VirumG2012	27738	140883	-	32183	17770	>6480	75.3	16	0.0	9	79111	*19486	29.7
VordingbG2009	8568	17025	5457	9905	5243	>6480	33.6	10	0.0	167	8972	*5787	32.5
Avg.							44.3		0.1	17.9			22.3

[†] An artificial bound on the amount of Halls' inequalities generated was enforced for tractability, see Section 4.3.

Table 2: Results summary. Note that rows 'Best solution' and 'Best bound' also counts draws.

	ALNS	3-index model	TSD	TSD ^{RoomLB}
Solution found	100	99	100	100
Best solution	77	2	8	18
Bound found	-	46	79	80
Best bound	-	13	19	49

Table 3: Comparison of the amount of best found solutions for the exact methods. Draws are also counted.

	3-index model	TSD	TSD ^{RoomLB}
Best solution	16	66	52

A number of conclusions can be drawn from the numbers:

- For 97 instances, the solution obtained by $\text{TSD}^{\text{RoomLB}}$ is at least as good as the solution obtained by the 3-index model, and for most instances significantly better.
- $\text{TSD}^{\text{RoomLB}}$ is generally the best method for generating bounds, finding the best bound on 49 instances overall.
- $\text{TSD}^{\text{RoomLB}}$ was capable of finding a lower bound for 80 instances. This means that for 20 instances, Gurobi was unable to solve the LP-relaxation of the root node of the Stage I model within the timelimit. Table 4 shows statistics for these instances (the presolved models). It is seen that the problems does not contain coefficients of huge magnitude in neither the objective, system matrix, or rhs. Hence the issue seems related to the relatively big number of constraints and variables. In average, these instances have more than 100000 constraints and variables, hence we think its fair to consider them as large-scale. Note that if the root-LP was not solved for an instance, the reported solution replicates the initial solution provided by us to Gurobi (Gurobi apparently starts its solution process by verifying the feasibility of the MIP Start attributes).
- $\text{TSD}^{\text{RoomLB}}$ produces the best solution for 18 instances overall, while TSD produces the best solution on 8 instances. The ALNS heuristic is best on 77 instances, and is currently the best algorithm for this problem (keep in mind the ALNS algorithm was allowed significantly less CPU time).
- Comparing the exact methods (Table 3), it is seen that it is generally not profitable to use the extended Stage I model if the goal is to obtain good solutions. Both variants of the decomposition finds more best solutions than the pure 3-index model.
- The Stage I model of $\text{TSD}^{\text{RoomLB}}$ is a challenge for Gurobi, with an average gap of 44.3% over all instances where a LB was found. Only 4 instances are solved to optimality, and these are among the smallest instances (see Sørensen and Stidsen (2013) for instance statistics).
- The Stage II model of $\text{TSD}^{\text{RoomLB}}$ is in general easy to solve. The average gap for this model over all problem instances is 0.1%, and 89 instances are solved to optimality. This means that future research can focus on solving the Stage I model.
- The difference between the lower bound on room allocation and the actual allocation of rooms (column 'Diff.') is low, compared to the magnitude of objectives in general. This means that only a small increase in solution quality can be gained by improving the bound on room allocation.

Table 4: Statistics of the Stage I models (after presolve) where Gurobi was unable to solve the LP-relaxation of the root-node within the timelimit (i.e. for those instances where the $\text{TSD}^{\text{RoomLB}}$ was unable to provide a lower bound). Column 'Cons.' shows the number of constraints and 'Non-zeros' shows the amount of non-zeros in the model. 'Variables' shows the amount of continuous, integer and binary variables. 'Obj. coef.', 'Model coef.', and 'RHS coef' shows the smallest and largest coefficient in the objective function, system matrix and right-hand side, respectively.

	Cons.	Non-zeros	Variables			Obj. coef.		Model coef.		RHS coef.	
			Cont.	Integer	Binary	Min.	Max.	Min.	Max.	Min.	Max.
Min.	73293	881433	24089	52518	41121	1	84	1	4	0	6
Max.	167978	4200206	52015	252514	246874	1	1120	1	16	1	103
Avg.	118396	1967455	36918	101460	88321	1	264	1	7	1	32

As an extension to the decomposition, one could use the ALNS heuristic to provide a starting solution. Since the ALNS heuristic is able to produce a fairly good solution quickly, this would most likely lead to improved performance.

As a loose remark, we mention that Burke et al. (2010) formulates an IP of the *Udine Course Timetabling Problem* (used in the International Timetabling Competition 2007), using a three-indexed binary variable, and reports that CPLEX 11 uses up to 6400 seconds when solving the root LP (using Dual Simplex, which is also used by Gurobi as default). Their model is quite similar in structure to ours, so possibly this class of IP formulations contain undesirable properties in the eyes of general-purpose MIP solvers.

7. Conclusion

A Two-Stage Decomposition for a real-world high school timetabling problem has been shown. This splits the Integer Programming model into two smaller models, which reduces the number of variables significantly. Computational results show that this approach is way more effective than solving the usual original IP with a 3-index binary variable, in terms of both the obtained solutions and the obtained bounds. This constitutes the TSD as the best exact method for solving this particular timetabling problem. However, the integration of the lower bound on room allocation in the Stage I model has bad influence on the quality of solutions, but makes the decomposition capable of achieving better lower bounds. Nevertheless this extension of the Stage I model represents interesting theory which can likely be used in the context of decomposing other timetabling problems.

For other types of (timetabling) problems, this type of decomposition might be a way of enhancing computational times. However, a special structure is required for applying the decomposition, which limits the set of applicable problems. On the other hand, the advantage gained by reducing the number of variables should not be underestimated, and we encourage researchers to attempt this type of decomposition if possible.

Approximating the room allocation penalties in the Stage I model is an interesting approach, and also sets a possible agenda for future work; 1) Can a better approximation (or even the exact value) be found for the minimum weight maximum matching problem representing room penalties? 2) Can the room stability penalties be incorporated in the Stage I model? However, the most important issue for future research is a more efficient way of solving the Stage I model. This is the bottleneck of the TSD for this particular problem.

References

- Avella, P., D'Auria, B., Salerno, S., Vasilâev, I., 2007. A computational study of local search algorithms for italian high-school timetabling. *Journal of Heuristics* 13, 543–556.
- Badri, M. A., 1996. A two-stage multiobjective scheduling model for [faculty-course-time] assignments. *European Journal of Operational Research* 94 (1), 16 – 28.
- Balas, E., Pulleyblank, W., 1983. The perfectly matchable subgraph polytope of a bipartite graph. *Networks* 13 (4), 495–516.
- Bardadym, V., 1996. Computer-aided school and university timetabling: The new wave. In: Burke, E., Ross, P. (Eds.), *Practice and Theory of Automated Timetabling*. Vol. 1153 of *Lecture Notes in Computer Science*. Springer Berlin / Heidelberg, pp. 22–45.
- Birbas, T., Daskalaki, S., Housos, E., 1997. Timetabling for greek high schools. *Journal of the Operational Research Society* 48, 1191–1200(10).
- Birbas, T., Daskalaki, S., Housos, E., April 2009. School timetabling for quality student and teacher schedules. *J. of Scheduling* 12, 177–197.
- Burke, E., Marecek, J., Parkes, A., Rudová, H., 2010. Decomposition, reformulation, and diving in university course timetabling. *Computers & Operations Research* 37 (3), 582–597.
- Burke, E., Newall, J. P., 1999. A multistage evolutionary algorithm for the timetable problem. *Evolutionary Computation, IEEE Transactions on* 3 (1), 63–74.
- Carter, M., 1983. A decomposition algorithm for practical timetabling problems. Tech. Rep. 83-06, Department of Industrial Engineering, University of Toronto.
- Daskalaki, S., Birbas, T., 2005. Efficient solutions for a university timetabling problem through integer programming. *European Journal of Operational Research* 160 (1), 106 – 120.
- Daskalaki, S., Birbas, T., Housos, E., 2004. An integer programming formulation for a case study in university timetabling. *European Journal of Operational Research* 153, 117–135.
- de Werra, D., 1985. An introduction to timetabling. *European Journal of Operational Research* 19 (2), 151 – 162.
- Dimopoulou, M., Miliotis, P., 2001. Implementation of a university course and examination timetabling system. *European Journal of Operational Research* 130 (1), 202 – 213.
- Edmonds, J., 1965. Maximum matching and a polyhedron with 0, 1-vertices. *Journal of Research of the National Bureau of Standards B* 69, 125–130.
- Egerváry, E., 1931. Matrixok kombinatorius tulajdonságairól. *Matematikai és Fizikai Lapok* 38, 16–28.
- Gotlieb, C. C., 1962. The construction of class-teacher timetables. In: Popplewell, C. M. (Ed.), *IFIP Congress*. Vol. 62. North-Holland Pub. Co, pp. 73–77.
- Lach, G., Lübbecke, M., 2008. Optimal university course timetables and the partial transversal polytope. In: McGeoch, C. (Ed.), *Experimental Algorithms*. Vol. 5038 of *Lecture Notes in Computer Science*. Springer Berlin / Heidelberg, pp. 235–248.
- Lach, G., Lübbecke, M., 2012. Curriculum based course timetabling: new solutions to udine benchmark instances. *Annals of Operations Research* 194, 255–272.
- Lawrie, N. L., 1969. An integer linear programming model of a school timetabling problem. *The Computer Journal* 12 (4), 307–316.
- Lovász, L., Plummer, M. D., 2009. *Matching Theory*. AMS Chelsea Publishing.
- MirHassani, S., 2006. A computational approach to enhancing course timetabling with integer programming. *Applied Mathematics and Computation* 175 (1), 814 – 822.
- Mittelman, H., Aug. 2013. Benchmarks for optimization software. <http://plato.asu.edu/bench.html> [Retrieved 20/8-2013].

- Papoutsis, K., Valouxis, C., Housos, E., 2003. A column generation approach for the timetabling problem of greek high schools. *The Journal of the Operational Research Society* 54 (3), 230–238.
- Pillay, N., February 2013. A survey of school timetabling research. *Annals of Operations Research*.
- Post, G., Ahmadi, S., Daskalaki, S., Kingston, J., Kyngas, J., Nurmi, C., Ranson, D., 2012a. An xml format for benchmarks in high school timetabling. *Annals of Operations Research* 194, 385–397.
- Post, G., Gaspero, L. D., Kingston, J. H., McCollum, B., Schaerf, A., August 2012b. The third international timetabling competition. In: *Proceedings of the Ninth International Conference on the Practice and Theory of Automated Timetabling (PATAT 2012)*. Son, Norway.
- Qualizza, A., Serafini, P., 2005. A column generation scheme for faculty timetabling. In: Burke, E., Trick, M. (Eds.), *Practice and Theory of Automated Timetabling V*. Vol. 3616 of *Lecture Notes in Computer Science*. Springer Berlin Heidelberg, pp. 161–173.
- Santos, H., Uchoa, E., Ochi, L., Maculan, N., April 2012. Strong bounds with cut and column generation for class-teacher timetabling. *Annals of Operations Research* 194 (1), 399–412.
- Schaerf, A., 1999. A survey of automated timetabling. *Artificial Intelligence Review* 13, 87–127.
- Schrijver, A., 2003. *Combinatorial optimization: polyhedra and efficiency*. Vol. 24 of *Algorithms and Combinatorics*. Springer.
- Sørensen, M., Stidsen, T., March 2013. Comparing solution approaches for a complete model of high school timetabling. Tech. Rep. 5.2013, DTU Management Engineering, Technical University of Denmark.